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Running head: TRAJECTORIES OF DEPRESSION IN OLD PEOPLE

Long-term trajectories of depressive symptoms in old age: relationships with sociodemographic and health-related factors

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Abstract

Background. This study aimed at depicting the course of depression symptoms over the old age, with a special interest in a) uncovering its relationships with sociodemographic and health-related factors; b) analysing its predictive role on healthy-ageing outcomes later in life. ***Methods.*** The sample comprised 8317 older adults (46.02% men) from the English Longitudinal Study of Ageing. Robust structural equation modelling was used to identify symptom trajectories and their relationships with time-varying factors. Trajectory class and covariates were used to predict outcomes (quality of life, satisfaction with life, and daily living functioning) in a 2-year follow-up. ***Results.*** Three trajectory classes (so-called, normative, subclinical, chronic symptom trajectories) were identified for both sexes. Rising hearing difficulties and history of psychiatric problems were consistently associated with the chronic symptom trajectory. Lower education level, history of psychiatric problems, and increasing visual difficulties were connected with the subclinical trajectories. Finally, participants with either a subclinical or a chronic symptom trajectory showed worse outcomes than the remaining participants in the follow-up. ***Conclusion:*** This study highlighted the presence of varying courses of depression symptoms (each showing some distinctive features from other another) over the old age, pointing to some relevant implications for clinical assessment and treatment prescription.

Keywords: Depression; longitudinal trajectories; mixture modelling; healthy ageing; measurement invariance

Long-term trajectories of depressive symptoms in old age: relationships with sociodemographic and health-related factors

Depression deserves special attention in late life, being one of the most prevalent psychiatric conditions. In the UK, studies have pointed out that almost three in ten people may show clinical levels of depressive symptoms over the old age (Andreas et al., 2017; Braam et al., 2014; Salk et al., 2017). Late-life depression is extensively associated with significant consequences, such as increased mortality, poor daily living functioning and substantial decrease in quality of life (Cuijpers et al., 2013; Damian et al., 2017; Sivertsen et al., 2015). Current models increasingly claim that depression should be tackled at its earliest stages, before full blown symptomatology becomes apparent (Woody & Gibb, 2015). In this sense, studies taking a symptom-level approach have stated the significant impact of clinically subthreshold depression on health-related outcomes over the old age and its individual-specific course (Carriere et al., 2011, 2016; Cuijpers et al., 2013; Salk et al., 2017).

Person-centred methods have highlighted the presence of varying, heterogeneous trajectories of depressive symptoms (Holmes et al., 2017; Hsu, 2012; Kuchibhatla et al., 2012). Recently, a systematic review has provided consistent evidence on depressive symptom trajectories, underlying the overall course, across the lifespan (Musliner et al., 2016). The authors showed that most longitudinal studies identified at least two trajectories of symptoms in the old age: one trajectory comprising most participants (normative trajectory class) and showing low levels of symptomatology; and another trajectory class comprising older adults with rising or persistently high levels of symptoms. However, findings were quite heterogeneous in terms of how many trajectories might exist. A potential explanation of these inconsistencies could be related

to divergences either in (see Carriere et al., 2016; Chui et al., 2015; Mirza et al., 2016): assessment protocols (e.g., some studies only approached young-old people), time effect conceptualisation (e.g., symptom trajectories were depicted by assessment wave, but not by age), analytical data approach (i.e., some individual-specific components scarcely approached by several analytical strategies used, such as latent class growth curve or low sample size). Byers et al. (2012) stressed that long-term investigation of depressive symptoms with robust methodology is needed, because most studies so far have been featured by short follow-up periods and overlooking older-old people, subsequently.

Many factors may be involved in how depression symptoms evolve over the old age. The most studied factor is gender. Sex-related differences in depression symptom manifestation and diagnosis rates have been systematically observed, probably because of sexually-mediated biological underpinnings, and socialisation influence (Colman et al., 2007; Salk et al., 2017). In this sense, old women often show higher levels of symptomatology than men, and steeper symptom increases over time (Chui et al., 2015; Hybels et al., 2013; Luppa et al., 2014).

Furthermore, sociodemographic features (i.e., marital status, level of formal education, household income), as well as psychosocial (loneliness, lifestyle behaviour) and health-related factors (history of psychiatric problems, presence of chronic diseases, sensory functioning) may be highly involved in the depiction of the depression symptom course in the late life. For instance, individuals with heightened trajectories of depressive symptoms may show antecedents of psychiatric problems in adulthood, more chronic diseases, basic education and lack of social support (Braam et al., 2014; Carriere et al., 2011; Chui et al., 2015; Hsu, 2012). Unfortunately, most studies have overlooked the time-varying nature of some of these factors over the old age. For instance, it is well known the accumulation of chronic diseases with age and its

increasing impact on depression, health-related outcomes and health care service utilisation (Calderon-Larranaga et al., 2018; Olaya et al., 2017; Patten et al., 2018). Also, a rising trajectory of sensory difficulties while becoming older is related to worse functioning and other health-related outcomes over time (Fritze et al., 2016; Lam et al., 2013).

This study aimed to identify heterogeneous longitudinal trajectories of depression symptoms over the old age (65 years and over) in men and women, separately. As highlighted in scientific literature, finding at least two different courses of depressive symptoms for both sexes (i.e., a course featured by low levels of symptoms and another course with rising symptoms over time) would be expected (Musliner et al., 2016). Additionally, it intended to study how some (cross-sectional or time invariant; and time-varying) factors may be related to the identified symptom trajectories. We hypothesised that participants with trajectories with higher levels of symptoms would show psychiatric problems in adulthood and steeper increase in sensory difficulties, as well as multimorbidity and loneliness, than participants comprising other trajectory classes. Finally, we were interested in analysing how trajectory class membership may predict health-related outcomes two years later (quality of life, satisfaction with life and daily living functioning). In this regard, it was expected that participants showing a trajectory of elevated symptoms (even in clinically subthreshold levels) over time would report worse quality of life and satisfaction with life; as well as greater impairment in daily living activities, in comparison to low-symptom trajectories.

Method

Data from the English Longitudinal Study of Ageing (ELSA) were used to satisfy the study aims (NatCen Social Research, 2012; Steptoe et al., 2013). ELSA

constitutes an ongoing population-based study comprising surveys every two years (along 14 years so far) since 2002. The target population was people aged 50 or over living in the UK. Refreshment samples were added in waves 3, 4, 6, and 7. By and large, ELSA aims at gathering relevant information on how people age, covering socioeconomic, environmental, and health-related aspects.

Sample

Data from 9483 respondents aged 65-90 years were used. None of them showed a diagnosis of dementia and completed the survey booklets by themselves (see the Supplementary material for further details on sample features). The men's sample comprised 4405 adults (mean age at wave 1 = 73.58, *sd* = 6.42), most of them married at wave 1 (72.65% of respondents), with either no formal qualification (25.39%), or secondary school qualification (25.97%); and mean of household income = £15831.33 a year (*sd* = 13613.45; range = 338654.10). On the other hand, the women's sample was composed of 5078 respondents (mean age at wave 1 = 74.45, *sd* = 6.78), most of them were either married (39.65% of respondents) or widowed (35.85%) at wave 1; with no formal qualification (39.34% of this sample) or secondary school qualification (23.23%); and mean of household income = £12242.69 a year (*sd* = £9370.99; range = 338654.10).

Depression symptoms

Depressive symptomatology was assessed in all waves (Table 1), by means of the Center for Epidemiologic Studies Depression Scale, 8-item version (CES-D 8; Karim et al., 2015; Turvey et al., 1999). This instrument is made up of eight items with a dichotomous (yes/no) scale of response. The CES-D 8 assesses the presence of key symptoms of depression disorders. Although the instrument was not made for depression diagnosis purpose, agreement between the CES-D 8 score and clinical

decisions based on standardised psychiatric interviews was well supported in older populations (Karim et al., 2015; Turvey et al., 1999). Thus, a cut-off point for clinical meaningfulness was set at 3 symptoms. Reliability indexes in our sample were appropriate across waves (Kuder-Richardson 20 index between .78 and .81).

Factor profile

Five time-varying factors were studied.

Self-reported health. Respondents graded their overall self-perceived health from 1 ('excellent') to 5 ('poor') across waves (Table 1).

Multimorbidity. An index consisting of the sum of diagnosed chronic conditions the respondent had was made. Participants reported whether a doctor had ever told them that they have any of these chronic conditions: hypertension, diabetes, cancer, chronic lung disease, arthritis, stroke and heart problems (i.e., angina, myocardial infarction, congestive heart failure, heart murmur, and arrhythmia).

Loneliness. The 3-Item UCLA Loneliness Scale (R-UCLA; Hughes et al., 2004) was used. The scale assesses how often an individual feels a lack of companionship, isolated and left out, by means of three items. Items ought to be responded using a 3-point scale (from 'hardly ever or never' to 'often'). A composite score is obtained from the items. Good reliability indexes were shown for the scale across survey waves (Cronbach's alpha between .82 and .83).

Hearing and visual function. Participants reported how well they hear (even using a hearing aid), by means of a 5-point scale (from 'excellent' to 'poor'). Also, their impression on their visual functioning (even using visual aids) was reported across waves.

Also, some *time invariant factors* were considered (Table 1): education level, household income, history of psychiatric problems in adulthood (conceptualised as

having received mental health treatment for either psychotic symptoms, anxiety, depression or mania) and age of retirement.

Outcomes

Quality of life. The CASP-19 composite score was used to measure quality of life (Hyde et al., 2003). This instrument is made up of 19 items with a 4-point scale of response (from 'often' to 'never'), covering four key domains of quality of life (control, autonomy, pleasure and self-realisation). Reliability index for the CASP-19 was acceptable (Cronbach's $\alpha = .89$).

Satisfaction with life. The 4-item version of the Satisfaction with Life Scale (SWLS-4; Pavot & Diener, 2008) was used. Each item is responded by means of a 7-point scale of response referring to how much the responder agreed with the item content (from 'strongly disagree' to 'strongly agree'). Reliability index for the SWLS-4 was very good (Cronbach's $\alpha = .90$).

Activities of daily living. An index accounting for difficulties to perform daily living activities was used (Katz et al., 1963). The index is ranged from 0 (no difficulties) to 6 (difficulties with all six activities). Reliability index for the activities of daily living index (ADL) was acceptable (Kuder-Richardson 20 index = .81).

Instrumental activities of daily living. The Instrumental activities of daily living index (IADL) aims at covering the difficulty a person could show when performing daily living activities necessary for functioning autonomously in community settings (for more details on instrumental activities of daily living, see Lawton, 1971). The index ranges from 0 (no difficulties) to 6 (difficulties with all six activities). The Reliability index for the IADL index was acceptable (Kuder-Richardson 20 index = .83).

(please, insert Table 1 here)

Analyses

Latent class mixed modelling (LCMM) was used for trajectory class enumeration (Proust-lima & Jacqmin-Gadda, 2005; Proust-Lima et al., 2017). LCMM allows the study of depression symptom trajectories underlying the overall course (see the Supplementary material). Trajectory class estimation was conducted in the sample of participants who did not show missing data in two consecutive survey waves. Model estimation involves considering the symptom trajectory over time free from the influence of potential covariates that may lead to class overestimation problems (see Diallo, Morin, & Lu, 2016; Vermunt, 2010). Model estimation relied on robust maximum likelihood and full information methods (this enabled the depiction of individual-specific trajectories even when intermittent missing data were present). Criteria to select the model with the optimal class enumeration were: low sample-adjusted Bayesian information criterion (SABIC), mean of posterior probabilities to belong to each class higher than .70; and meaningful proportion of participants within each class (5%).

The sample of participants who responded to at least three out of the four initial waves (from wave 1 to 4) was used to conduct a profile analysis. Multiple imputation methods were used to estimate data when values were missing only in one wave (Brand, 1999). Two methodologies based on measurement invariance (MI) were used for profile analysis (Kievit et al., 2018; Meredith & Teresi, 2006; Widaman et al., 2010): multigroup latent growth curve analysis (MLGC) to study the scores and changes between consecutive waves in factors measured across more than two waves (Table 1); and multigroup change score analysis (MCS) for loneliness. The multigroup factor was the trajectory class membership. Thus, we compared the goodness of fit of structural

solutions adding parameter constraints (i.e., in order to make parameter being equal across groups) one at a time (see the Supplementary material for further details).

Model estimation relied on diagonally weighted least squares methods, except for loneliness (i.e., robust maximum likelihood methods). Model fit was studied by the scaled χ^2 statistic, the root mean square error of approximation index of .08 or lower; and comparative fit index (CFI) and Tucker-Lewis index (TLI) higher than .95. Comparisons between the nested MI models were conducted using the incremental CFI (ΔCFI), according to Meade et al. (2008) recommendations. Values of $\Delta CFI < -.002$ would reflect a lack of MI (i.e., trajectory class of symptoms might mediate on levels and/or change across waves).

Multinomial regression was used to study the predictive role of time invariant factors on trajectory class membership. A lower Akaike information criterion (AIC) for the model with profile factors (in comparison to unconstrained models) was expected. *Z*-based Wald tests were used to prove significantly different from zero factor loading. The Cragg and Uhler's R^2 was considered as the effect size estimate.

Finally, generalised linear regression was approached to study outcome prediction (i.e., how trajectory class membership may predict outcomes at wave 6). In this sense, some health-related factors were also included as predictors: latent change scores when a lack of MI was upheld, age at wave 6, history of psychiatric problems and antidepressant prescription at wave 6. Models with covariates were compared to unconstrained models and the related AIC was calculated. *Z*-based Wald tests were also used to prove significance of factor loadings.

All the analyses were conducted using stata (multinomial regression) and R software (R Core Team, 2018) and packages lcmm (trajectory class enumeration), lavaan (measurement invariance analyses) and mice (missing data imputation).

Results

After removing participants with at least two consecutive waves without depression symptom data, sample in analysis comprised 8317 participants (3828 men, with mean initial age = 73.49, *sd* = 6.39; and 4489 women, with mean initial age = 74.26, *sd* = 6.67). Further details and descriptive statistics on relevant factors are included in the Table S1 (see the Supplementary material). Figure 1 displays the flow diagram of sample included in each analysis.

(please, insert Figure 1 here)

Trajectory class enumeration

The mixture solution comprising three heterogeneous trajectories with linear growth on the fixed and mixture components showed a better fit to data (in comparison to nested models), for both sexes (see the Table S2 in the Supplementary material). Fit indexes were low (SABIC = 36917.51 for men model, SABIC = 50853.62 for women model) and means of posterior probabilities of belonging to each of the three trajectory classes were very good for the men's sample (between .83 to .96) and for the women's sample (between .78 to .91). Thus, most participants comprised the so-called normative trajectory class (77.35% of men and 68.21% of women, respectively), with slight symptom growth over time (time effect with slope, $B = 0.02$, $SE = 0.00$, $p < .05$, for both sexes). Levels of symptoms in participants showing this symptom trajectory remained low over time (never approaching the level of clinical meaningfulness). Also, a trajectory class (the so-called subclinical trajectory class) comprising individuals with increasing levels of symptoms was found (16.64% of men and 21.25% of women, respectively). Symptoms surpassed the cut-off point of clinical meaningfulness over

time in this class (time effect with slope, $B = 0.04$, $SE = 0.00$, $p < .05$, for men; and $B = 0.03$, $SE = 0.00$, $p < .05$, for women). Finally, it identified a class (the so-called chronic symptom trajectory class) of participants (6.01% of men and 10.54% of women) who showed heightened levels of symptoms over time (see Table S3 for factor loadings within each class). Symptom level remained clinical and stable over time (as no time effect was found, with $p > .05$, for both sexes) in this class. Sex-specific trajectories by class are displayed in the Figure 2.

(please, insert Figure 2 here)

Factor profile

In order to check the absence of overlap between morbidity and sensory function and depression symptoms in old age, correlation analyses were conducted. As a result, weak correlations were observed across waves: Pearson's *r* from .16 at wave 3 and .22 at wave 1, regarding the multimorbidity index and CES-D 8; Spearman's ρ between .15 (CES-D 8 at wave 1 and visual function at wave 4) to .23 (CES-D 8 at wave 5 and visual function at wave 4), for the relationship between depression symptoms and vision; and Spearman's ρ between .06 (CES-D 8 at wave 1 and hearing function at wave 4) to .14 (CES-D 8 at wave 5 and hearing function at wave 4), for the relationship between depression symptoms and hearing.

MI models revealed significantly different growth slopes across trajectory classes in both sexes, as proven by the lack of MI observed only when the latent variable slope (related to changes between consecutive waves) was constrained (see Table S4). Regarding the men's sample, participants comprising the chronic symptom trajectory class showed steeper growth in multimorbidity ($B = 0.27$, $SE = 0.05$; $z = 5.75$,

$p < .01$) and hearing difficulties ($B = 0.12$, $SE = 0.05$; $z = 2.23$, $p < .03$); as well as higher decrease in loneliness ($B = -0.50$, $SE = 0.17$; $z = -2.97$, $p < .01$). Men from the subclinical trajectory class exhibited a stronger growth of visual difficulties ($B = 0.10$, $SE = 0.02$; $z = 4.19$, $p < .01$) than those from the other classes (see Figure 3).

(please, insert Figure 3 here)

On the other hand, women from the chronic symptom trajectory class showed a steeper rising of hearing difficulties ($B = 0.10$, $SE = 0.03$; $z = 3.17$, $p < .01$) than those from the other classes; subclinical trajectory class women displayed a higher increase of multimorbidity ($B = 0.21$, $SE = 0.01$; $z = 17.38$, $p < .01$) and visual difficulties ($B = 0.10$, $SE = 0.02$; $z = 4.90$, $p < .01$). Finally, normative class participants showed a higher growth rate in self-reported health ($B = 0.12$, $SE = 0.01$; $z = 11.21$, $p < .01$).

Multinomial regression revealed that the predictive role of cross-sectional profile factors on class membership for both sexes (model for men, with AIC = 508.71 and $R^2 = 0.11$; and for women, AIC = 766.97 and $R^2 = 0.06$) than the unconstrained models (AIC = 1541.64 and $R^2 = 0.00$, for men; AIC = 2925.80 and $R^2 = 0.00$, for women). The subclinical class membership was explained by the history of psychiatric problems (relative risk ratio = 9.82, *CI95* = 3.27, 29.47; $z = 4.07$, $p < .01$) in men. On the other hand, the subclinical class membership in the female sample was explained by the household income (relative risk ratio = 0.99, *CI95* = .99, 1.00; $z = -2.19$, $p < .03$). No significant cross-sectional predictors were related with the clinical trajectory class membership for both sexes.

Outcome prediction

Generalised linear regressions revealed that quality of life at wave 6 was significantly explained by an intercept, the class membership and age at wave 6 in both sexes (see Table 2). The antidepressant prescription also showed a significant explanatory role on this outcome for women. Satisfaction with life was explained in male participants by the intercept, trajectory class membership and age at wave 6. Conversely, this outcome was only explained by the intercept and class membership.

(please, insert Table 2 here)

Regarding functioning outcomes, ADL in male sample was explained by the intercept and changes in loneliness across waves; and IADL by trajectory class membership and age at wave 6. On the other hand, ADL and IADL was explained by class membership, age and antidepressant prescription in the sample of female respondents (Table 2). It is worth mentioning that antidepressant prescription was significantly different across trajectory classes only in the sample of female older people, χ^2 (2) = 15.48, $p < .01$ (24.61% of women from the chronic symptom trajectory class had antidepressant prescription, in comparison with 13% and 9% of those from the subclinical and normative classes, respectively). Figure 4 displays how outcomes were distributed across trajectory class membership.

(please, insert Figure 4 here)

Discussion

This study aimed to provide some evidence on how depression symptoms evolve in old age. Relying on longitudinal person-centred methods, it intended to identify

heterogeneous trajectories for both sexes. Moreover, we were interested in studying the relationship between some sociodemographic and health-related factors (factor profile), highly connected with depression disorders, and sex-specific trajectories. Finally, it aimed to study how the varying longitudinal courses of symptoms might explain healthy-ageing outcomes (quality of life, satisfaction with life, ADL and IADL), later in life.

Findings derived from this study highlighted that since depression symptoms were increasingly higher over time, heterogeneous trajectories should be considered. Concretely, we identified three different trajectories of symptoms for both men and women (i.e., the so-called normative, subclinical symptom and chronic symptom trajectories). Our results go in line with some assumptions already well-supported in scientific literature (Carriere et al., 2016; Kaup et al., 2016; Luppa et al., 2014; Montagnier et al., 2014; Musliner et al., 2016): 1) sex-specific differences in trajectory membership (i.e., more proportion of women showing subclinical and chronic symptom trajectories in comparison to men); 2) most of the participants showed low levels of symptoms (more than 65% in our samples); 3) chronic symptomatology was quite infrequent among old people (6.01% of men and 10.54% of women). Interestingly, participants depicting a chronic symptom trajectory showed heightened levels of symptoms over the old age (and probably in earlier periods of life). The other trajectory classes showed increasing levels of symptoms over time.

Regarding the factor profile, the history of psychiatric problems was proved to be consistently associated with rising symptom trajectories, in line with other studies (Carriere et al., 2016; Hsu, 2012; Montagnier et al., 2014; Musliner et al., 2016). Moreover, we found that chronic symptom trajectory class membership was associated with a higher increase in hearing difficulties and multimorbidity, probably because of

reward loss on a daily basis (e.g., difficulty in holding conversations), regardless of sex (Brewster et al., 2018; Rote et al., 2015). On the other hand, subclinical trajectory class membership was distinguished by a higher increase in visual difficulties over time probably due to a moderate loss of reward (i.e., visual impairment limits independence) and sensory disability (Freeman et al., 2016; Tolman et al., 2005).

Interestingly, sex-specific relationships with some factors and symptom trajectories were found. In women, a higher amount of multimorbid conditions over time was linked with showing a rising symptom trajectory. Robust studies have shown a strong relationship between the onset of depression syndromes and multimorbidity, especially related to disease management and functional and social role losses (Carayanni et al., 2012; Chui et al., 2015; Marengoni et al., 2011).

Regarding men, a higher number of multimorbid conditions over time was related to chronic symptom trajectory class membership. Feelings of being less useful on a community and family (i.e., difficulty in multimorbidity management) bases seem to have a crucial role on maintaining heightened depression symptomatology in men. Additionally, old men may show many difficulties to adjust themselves to live alone due to widowhood and feelings of loneliness may emerge. For that reason, they tended to look for a new partner more frequently than women (see Girgus et al., 2017). Our results in loneliness changes across waves may go in this line: the proportion of men who were widowed in wave 3 (3.95%) was slightly higher in comparison to wave 4 (3.64%); conversely, the proportion of men with a civil partner rose from wave 3 (0.82%) to wave 4 (1.29%).

Finally, this study provided some valuable evidence on how depression symptom trajectory would have an impact on some healthy-ageing outcomes later in life, even after controlling for profile factors and age. We found that participants,

regardless of sex, with either a chronic symptom or subclinical trajectory manifested lower quality of life and satisfaction with life than normative-trajectory participants; they also manifested higher ADL (only women) and IADL difficulties. This goes in line with the idea of overcoming traditional diagnosis-based approaches and addressing psychiatric conditions from earlier stages (Woody & Gibb, 2015; Schoevers et al., 2006). Subthreshold depression is responsible for changes in brain structures involved in emotion and cognition, and may be a risk factor for severe diseases and increased mortality (Chang et al., 2017; Cuijpers et al., 2013; Zhou et al., 2016).

To summarise, this study aimed at uncovering the heterogeneous, person-specific nature of depression symptom course throughout the late life period. Our results relied on a robust, longitudinally-based methodology (i.e., trajectories modelled by means of age and time-varying profile factors were addressed), with a large sample of a nationally representative cohort of older adults. Furthermore, trajectories were modelled by sex. Finally, trajectory class enumeration was based on latent constructs and not on pre-established, arbitrary conceptualisations.

On the other hand, this study had some shortcomings worth mentioning. Firstly, study variables were taken from self-reported items. Self-reported symptoms and health conditions have been shown as reliable proxies of actual states and diagnoses, but some considerations should be taken to ensure their accuracy (see Pettersson et al., 2015; Stockings et al., 2015; Stone et al., 2000). In this sense, we reported psychometric properties of the self-reports used in this study, stating adequate levels of validity and reliability. However, further research should be done with objective tests in order to complement findings from this study. Furthermore, cognitive decline was not assessed in our sample. This may be associated with depression symptoms. In this sense, we came from a free-dementia sample, discarding the effect of severe cognitive decline on

our data. However, stronger controls on cognitive decline should be taken in further research. Also, factor profile and prediction outcome analyses comprised lower sample size in comparison to class enumeration ones. In this regard, no missing data is permitted across waves when modelling MI solutions and generalised regression. However, attrition analyses showed no significant differences between respondent and non-respondent participants in terms of sociodemographic and health-related factors. On the other hand, the use of aids (e.g., hearing aids, glasses) was not recorded in this study. Even though, we were interested in studying the impact of sensory disability on a daily basis (for that reason, assessing individual's impression on sensory functioning even using aids). The use of aids is common in western countries and almost available to everyone. Therefore, aids enable functional independence being recovered (or at least, partially) and sensory function improved.

Depression is a global health priority. This study constitutes an attempt to raise awareness of personalised medicine and its potential. For that reason, very useful implications in terms of clinical assessment and treatment prescription may be derived. Firstly, a mention on tailored protocols is mandatory. We identified different symptom trajectories and related profile factors. Clinicians and researchers should consider person-specific and longitudinal issues to make decisions on diagnosis and clinical profiles more accurate. In this regard, a patient showing depression symptoms due to, for instance, the death of a relative and low level of community participation may present a very characteristic profile in comparison to a person exhibiting depression symptoms chronically. Therefore, therapeutic choice should be guided by patient profile. Moreover, therapeutic options addressing modifiable health-related factors (e.g., sensory aids or behavioural interventions promoting healthy lifestyles) may hinder the escalation of depression symptoms across the old age. Secondly, prevention (e.g.,

initiatives aimed at raising the awareness of the importance of healthy eating and adequate exercise in the middle age) should be a lifelong imperative to prevent the burden of depression in the old age and its related impact. Finally, clinicians and health and social policy makers should make higher efforts to deal with late-life depression from earlier syndromic states due to its prevalence (almost 25% of older adults reached clinically meaningful symptoms over the course of their lifetime) and impact on quality of life and daily functioning.

Funding and conflict of interests

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Conflict of interests: none.

Availability of data and materials

Data are available on ELSA webpage (http://elsa-project.ac.uk). Details on complementary analyses and results are available upon corresponding author request.

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Table 1. **Timetable of the ELSA study across survey waves.**

	Wave 1 (2002/03)	Wave 2 (2004/05)	Wave 3 (2006/07)	Wave 4 (2008/09)	Wave 5 (2010/11)	Wave 6 (2012/13)
Depression symptoms*	X	X	X	X	X	
Profile factors						
Self-reported health	X	X		X		
Multimorbidity	X	X	X	X		
Loneliness**			X	X		
Hearing function	X	X	X	X		
Visual function	X	X	X	X		
Education level•	X					
Household income	X					
History of psychiatric problems	X					
Age of retirement					X	
Outcomes						
Quality of life†						X
Satisfaction with life‡						X
ADL						X
IADL						X

Note. * Measured by the Center for Epidemiologic Studies Depression Scale, 8-item version (CES-D 8); ** Measured by the 3-Item UCLA Loneliness Scale (R-UCLA).

• Categories considered: no qualification mentioned; up to secondary school; secondary school graduate; some college education; college graduate or above.

† Assessed by the CASP-19 questionnaire; ‡ Assessed by the 4-item version of the Satisfaction with Life Scale (SWLS-4).

ADL = Activities of daily living; IADL = Instrumental activities of daily living.

Table 2. **Outcome prediction (at wave 6) according to sex.**

Predictor	Men				Women			
	Quality of life	Satisfaction with life	ADL	IADL	Quality of life	Satisfaction with life	ADL	IADL
(Intercept)	72.76 (11.12)***	52.12 (8.32)***	-2.63 (0.70)***	-1.15 (0.71)	61.46 (7.67)***	30.31 (5.79)***	-0.71 (0.56)	-1.97 (0.52)***
Trajectory class membership								
Linear effect	-5.06 (1.21)***	-4.33 (0.98)***	0.12 (0.09)	0.12 (0.09)	-4.29 (0.71)**	-2.91 (0.55)**	0.20 (0.05)***	0.23 (0.05)***
Quadratic effect	5.16 (4.41)	0.83 (3.35)	-0.18 (0.33)	-0.89 (0.09)**	8.03 (1.44)**	5.18 (1.01)	-0.34 (0.09)***	-0.28 (0.08)**
Age at wave 6	-0.48 (0.13)***	-0.36 (0.10)***	0.04 (0.01)***	0.02 (0.01)*	-0.32 (0.09)***	-0.09 (0.01)	0.02 (0.01)*	0.03 (0.01)***
Antidepressant prescription	-0.52 (2.13)	1.02 (1.66)	-0.02 (0.16)	0.23 (0.16)	-3.28 (1.57)*	-1.17 (1.12)	0.30 (0.10)**	0.25 (0.09)**
Household income†					-0.01 (0.01)	-0.00 (0.01)	-0.00 (0.01)	-0.00 (0.01)
Psychiatric history†	3.60 (3.24)	4.23 (2.47)	-0.09 (0.24)	-0.14 (0.24)				
Loneliness change†‡	0.54 (0.75)	0.05 (0.60)	-0.15 (0.05)**	0.04 (0.05)				
Hearing difficulty change‡	3.81 (7.88)	2.31 (5.98)	0.19 (0.53)	0.49 (0.54)	-6.66 (4.09)	0.19 (3.11)	0.04 (0.30)	0.06 (0.28)
Visual difficulty change‡	-5.13 (7.72)	1.58 (5.85)	0.40 (0.53)	0.93 (0.54)	-0.36 (2.96)	-1.50 (2.23)	0.10 (0.22)	0.20 (0.20)
Multimorbidity change‡	0.86 (2.33)	0.02 (1.76)	0.01 (0.16)	-0.16 (0.16)	-2.31 (1.55)	-0.41 (1.17)	-0.05 (0.11)	-0.01 (0.10)

Note. Factor loading and standard error (between brackets) are displayed by outcome.

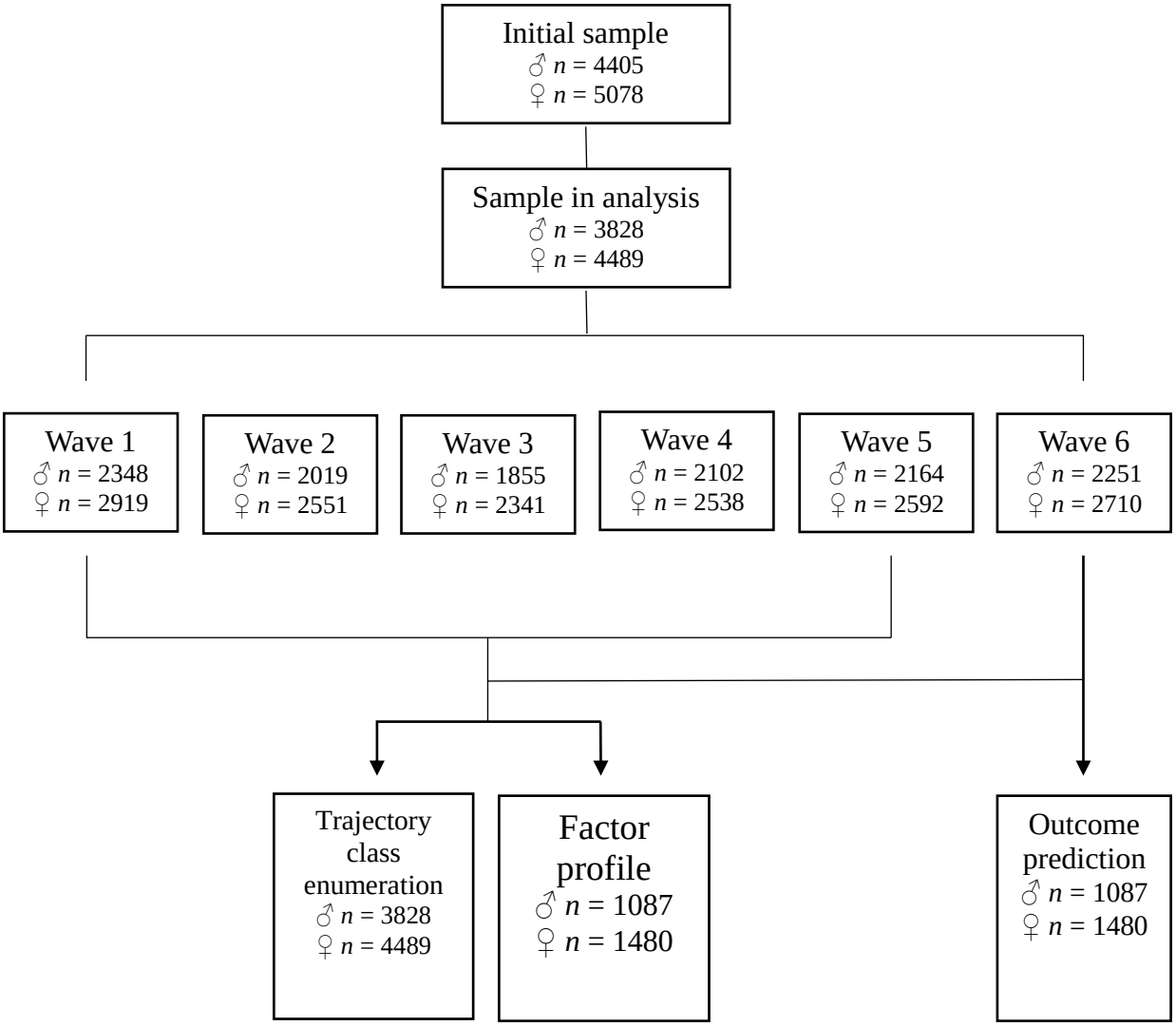
Quality of life was assessed by the CASP-19 questionnaire. Satisfaction with life was assessed by the 4-item version of the Satisfaction with Life Scale (SWLS-4). ADL = Activities of daily living. IADL = Instrumental activities of daily living.

† Factors that showed sex-specific different scores across depression trajectory classes

‡ Latent scores of change across waves (taken from the measurement invariance models).

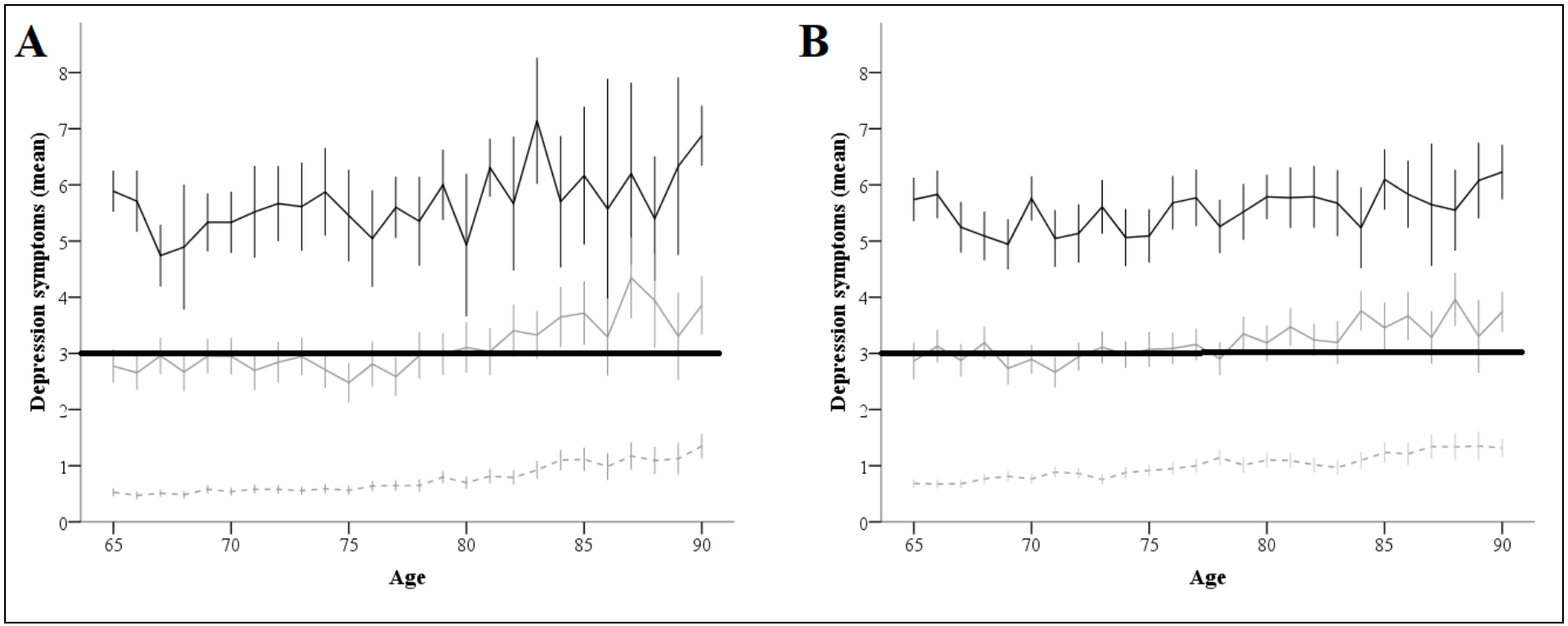
* $p < .05$; ** $p < .01$; *** $p < .001$.

Figure 1. **Flow diagram of sample included in analyses.**



Note. ♂ = sample of men. ♀ = sample of women.

Figure 2. **Class-specific trajectories of depression symptoms by sex.**

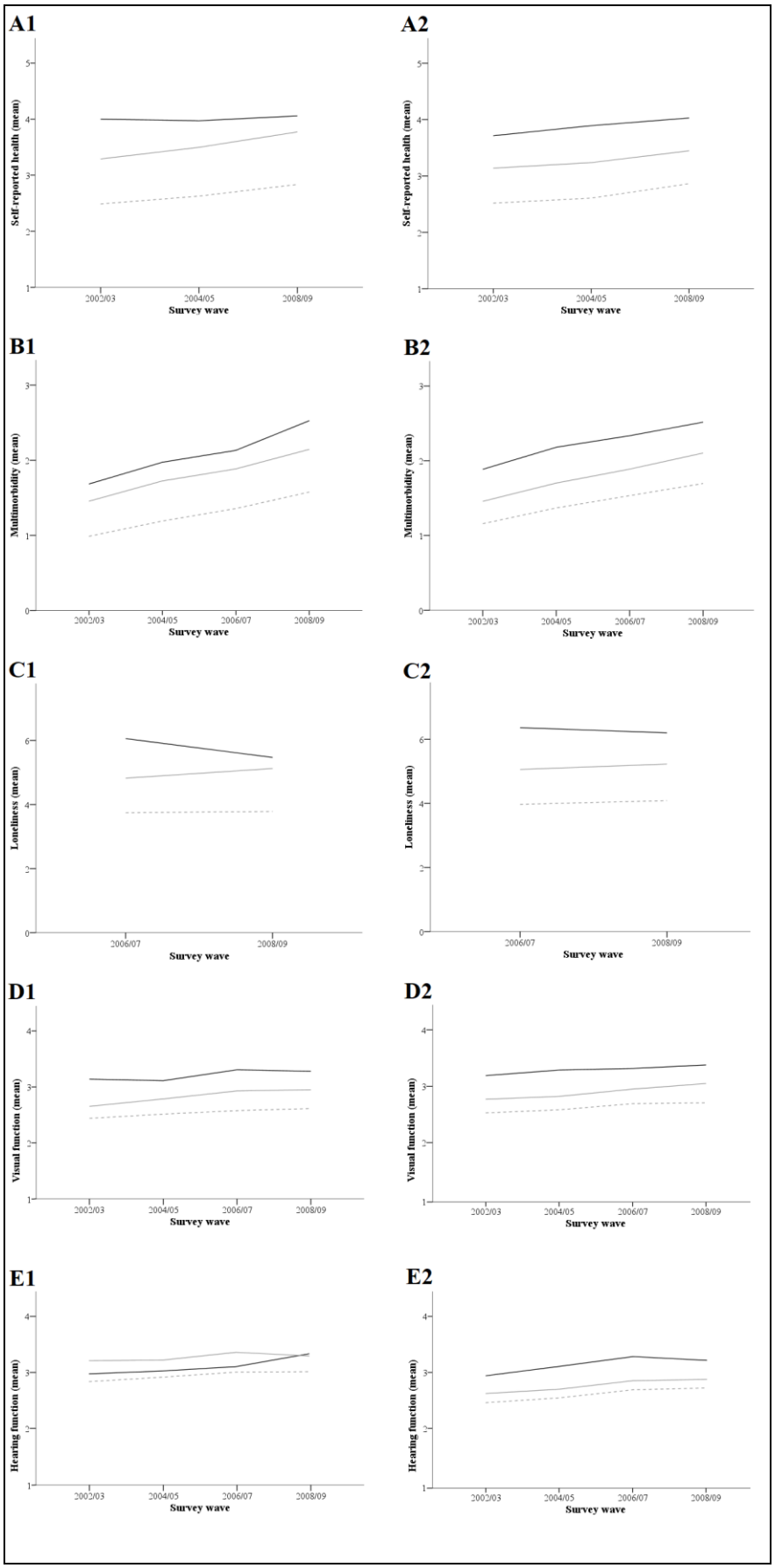


Note. The A box displays the class-specific trajectories for male participants. The B box displays the class-specific trajectories for female participants.

Thick dark line depicts the cut-off point for clinical meaningful level of symptoms (CES-D 8 ≥ 3 involves clinical levels of symptomatology according to Turvey et al., 1999). Error bars depict the 95% confidence interval of the mean.

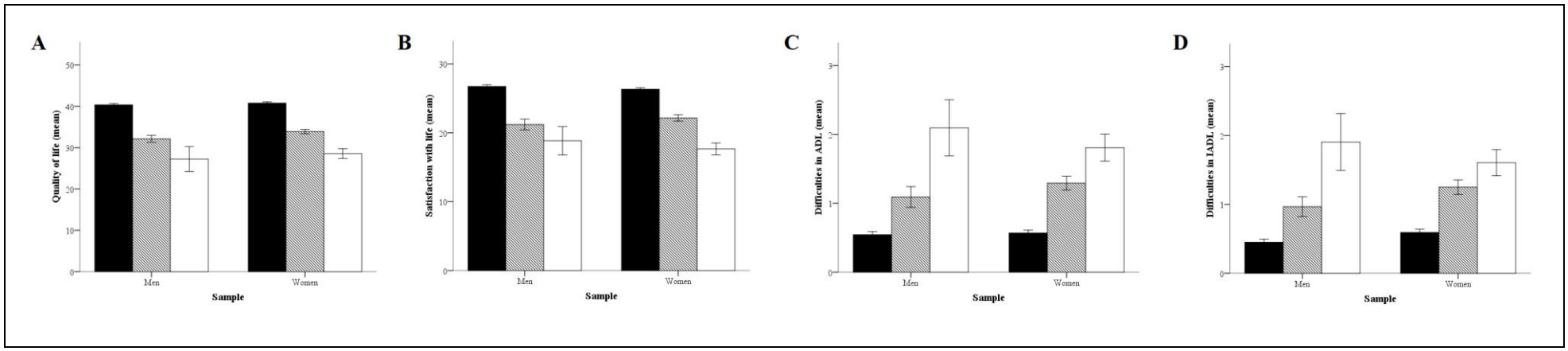
Dashed grey line = normative trajectory class. Solid grey line = subclinical trajectory class. Solid dark line = chronic symptom trajectory class.

Figure 3. **Class-specific trajectories of time-varying risk factors by sex.**



Note. Boxes A = class-specific trajectories of self-reported health (from 1, ‘excellent’, to 5 ‘poor’). Boxes B = trajectories of multimorbidity across survey waves. Boxes C = trajectories of loneliness across waves. Boxes D = class-specific trajectories of self-reported visual function (from 1, ‘excellent’, to 4 ‘poor’). Boxes E = trajectories of self-reported hearing function (from 1, ‘excellent’, to 4 ‘poor’).
Boxes 1 = trajectories for male participants. Boxes 2 = trajectories for female participants.
Dashed grey line = normative trajectory class (n = 1021, for the male sample; n = 1149, for the female sample). Solid grey line = subclinical trajectory class (n = 216, for the male sample; n = 436, for the female sample). Solid dark line = chronic symptom trajectory class (n = 45, for the male sample; n = 157, for the female sample).
Error bars are not provided due to overlapping between scores across classes.

Figure 4. **Class-specific scores of outcomes measured at wave 6 by sex.**



Note. Box A = class-specific scores in quality of life. Box B = class-specific scores in satisfaction with life. Box C = class-specific scores in difficulties in activities of daily living (ADL). Box D = class-specific scores in difficulties in instrumental activities of daily living (IADL). Error bars depict the standard error of the mean.

Dark bar = normative trajectory class participants (n = 719, for the male sample; n = 817, for the female sample). Grey bar = subclinical trajectory class participants (n = 120, for the male sample; n = 300, for the female sample). White bar = chronic symptom trajectory class participants (n = 21, for the male sample; n = 99, for the female sample).

Significant differences were found in all the outcomes between the participants from the clinical classes and those from the normative classes ($p < .01$); and between the participants from the clinical classes and those from the normative classes ($p < .01$).

Supplementary material

Method

Sample.

We excluded participants aged more than 90 because of ELSA coding features (i.e., all respondents aged 90 or over were coded with a value of 99 due to confidentiality reasons; see NatCen Social Research, 2012).

Overall response rates by wave were: wave 1 = 88.50%; wave 2 = 71.45%; wave 3 = 63.63%; wave 4 = 66.34%; wave 5= 61.84%; wave 6 = 56.45%.

Descriptive statistics regarding the sample in analysis (sample without missing data in two consecutive waves, regarding depression symptomatology) are displayed in Table S1. Attrition analyses revealed no differences between the initial sample and sample in analysis, in terms of sociodemographic and health-related factors.

To satisfy the second and third study aims, a sample of 2567 respondents (i.e., those who responded in at least three surveys and remained alive in wave 5) was used. Attrition analyses revealed that participants of this sample was older (mean age at wave 1 = 72.45, *sd* = 5.75; mean age for non-respondents = 68.48, *sd* = 9.35) and with lower household income (mean income at wave 1 = £14766.77, *sd* = 14081.74; mean income for non-respondents = £16828.61, *sd* = 20849.81). No differences between respondents and non-respondents were found in terms of health-related variables. Multiple imputation procedures allowed for estimating missing data values. As a result, 1987 values were imputed (2.63% of total data). Variables with imputed values showed similar distribution than original data (see Figure SF1). Male sample comprised 1087 participants, with mean age at wave 1 = 71.94 years (*sd* = 5.48), most of them married (81.58% of participants) and without any formal qualification certificate (49.21% of

participants). Female sample was composed of 1480 respondents, with mean age at wave 1 of 72.83 years (*sd* = 5.93), most of them married (51.64%) and without any formal qualification certificate (69.37%).

Factor profile.

Score polychoric correlations for self-reported health were between .60 to .68 across survey waves. Polychoric correlations between the multimorbidity indexes across waves were.79 to .90. On the other hand, polychoric correlations between the multimobidity index and self-reported health across waves were moderate (from .39 between the 4th-wave self-reported health and the 4th-wave multimorbidity index; to .53 between the 1st-wave self-reported health and the 2nd-wave multimorbidity index).

Considering loneliness, the Pearson's correlation between the R-UCLA scores across waves was .68. Finally, hearing and visual function items showed moderate polychoric correlations across waves (.63 to .71 for hearing function, and .42 to .58 for visual function).

Correlation between profile factors are displayed in Figure SF2 in order to test for collinearity assumption. As a result, low-to-moderate correlations were found between predictors (except for scores from a same factor measured across waves) discarding either the effect of collinearity or predictor interaction effects.

Outcomes.

The ADL index was made using self-reported indicators of performance on five daily activities: bathing, dressing, walking across a room, eating, getting in or out of bed and using a toilet.

The IADL index was created using the self-reported performance item of six instrumental activities: using a map, preparing a hot meal, shopping in groceries, making telephone calls, taking medications and managing your money.

Analyses.

The latent process to be studied within the LCMM was the trajectory of depression symptoms over the old age, using age (not wave) as a time variable. Model estimation involves considering the symptom trajectory over time free from the influence of potential covariates that may lead to class overestimation problems (see Diallo, Morin, & Lu, 2016; Vermunt, 2010). Solutions with increasing trajectory classes were tested. Also, linear and quadratic effects of the fixed, random and class-specific (mixture) components were explored. A solution may fit better to data when showing smaller values of sample-adjusted Bayesian information criterion (SABIC). Also, mean of posterior probabilities of belonging to every trajectory class should be higher than .70; and each class should have a meaningful percentage of participants (at least, 5% of sample).

In terms of MI analyses, MLGC allows for studying basal levels and change over time, as two latent constructs are assumed to depict a longitudinal course or trajectory (level and slope, respectively). Conversely, MCS relies on testing change between scores in two consecutive time points; hence, a latent factor (slope) was studied. We compared the goodness of fit of increasingly constrained solutions for each factor: a configural solution (assuming the same overall pattern of relationships between variables across groups), weak invariance solution (constraints on loadings of latent variables to be equal across groups; only tested in MCS due to MLGC model specifications), strong invariance (adding constraints on threshold and observable intercepts to be equal across groups) and strict invariance (adding constraints on latent and observable variances and covariances to be equal across groups). Partial MI (i.e., adding constraints on one of the latent factor, level or slope, or on both) was used for

MLGC solutions. On the other hand, multinomial logistic regression estimation was based on ordinary least squares methods.

Finally, we opted for using generalised linear regression, also relied on ordinary least squares method of estimation, due to its flexibility to study outcomes with non-normal distributions. In this regard, quality of life and satisfaction with life models were conducted assuming a Gaussian outcome distribution (as outcomes showed multivariate normality) and ADL and IADL assuming a gamma outcome distribution. Covariates (besides age at wave 6, history of psychiatric problems and antidepressant prescription at wave 6) were the latent change in hearing difficulties, visual difficulties, multimorbidity and loneliness (only in the case of men).

Tables

Table S1. Descriptive statistics across waves.

	Wave 1		Wave 2		Wave 3		Wave 4		Wave 5		Wave 6	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Age	73.49 (6.39)	74.26 (6.67)										
Depression symptoms[*‡]	1.33 (1.78)	1.83 (2.06)	1.29 (1.73)	1.86 (2.06)	1.22 (1.73)	1.82 (2.09)	1.10 (1.69)	1.74 (2.04)	1.26 (1.76)	1.81 (2.03)		
Profile factors												
Self-reported health[**]	2.87 (1.13)	2.86 (1.10)	2.92 (1.12)	2.92 (1.11)			2.92 (1.10)	2.98 (1.08)				
Multimorbidity	1.19 (1.08)	1.28 (1.09)	1.35 (1.13)	1.47 (1.13)	1.46 (1.17)	1.58 (1.15)	1.48 (1.20)	1.62 (1.16)				
Loneliness[***]					3.99 (1.41)	4.40 (1.66)	3.99 (1.42)	4.38 (1.63)				
Hearing function[**]	2.85 (1.16)	2.51 (1.14)	2.91 (1.14)	2.57 (1.12)	2.98 (1.11)	2.66 (1.10)	2.96 (1.11)	2.64 (1.09)				
Visual function[**]	2.56 (0.99)	2.69 (1.01)	2.56 (0.97)	2.69 (0.98)	2.63 (0.98)	2.76 (0.98)	2.54 (0.98)	2.70 (0.99)				
Education level												
No qualification	33.56	47.78										
Up to secondary school	25.43	20.97										
Secondary school graduate	11.28	12.64										
Some college education	16.09	12.08										
College graduate	13.64	6.53										
Household income	18112.99 (22769.51)	14260.26 (13692.73)										
History of psychiatric problems	3.28	5.11										

(% yes)				
Age of retirement	61.45 (5.26)	57.80 (8.63)		
Outcomes				
Quality of life†			16.63 (8.55)	16.97 (8.53)
Satisfaction with life‡			14.09 (6.23)	14.80 (6.32)
ADL			0.48 (1.15)	0.62 (1.28)
IADL			0.36 (1.08)	0.54 (1.28)

Note. Means and standard deviations (between brackets) are displayed for quantitative factors; and percentage of cases for categorical/dichotomous factors.

* Measured by the Center for Epidemiologic Studies Depression Scale, 8-item version (CES-D 8); ** Scores range from 1 ('excellent') to 5 ('poor') in all the waves; *** Measured by the 3-Item UCLA Loneliness Scale (R-UCLA).

† Assessed by the CASP-19 questionnaire; ‡ Assessed by the 4-item version of the Satisfaction with Life Scale (SWLS-4).

ADL = Activities of daily living; IADL = Instrumental activities of daily living.

‡ A main effect was observed for this factor in terms of sex, F (1, 28386) = 673.90, $p < .01$; and wave, F (1, 28386) = 97.90, $p < .01$.

Table S2. Comparison summary to select the model with the optimal class enumeration by sex.

Men					
Number of trajectory classes	model specifications*	Loglik	BIC	SABIC	% participants in classes
1	Squared growth on fixed component and linear growth on random component	-19253.96	38565.68	38543.44	
1	Linear growth on fixed and random components	-19280.52	38610.55	38591.49	
1	Squared growth on fixed component	-19285.46	38612.16	38596.28	
1	Linear growth on fixed component	-19312.19	38657.37	38644.66	
1	No growth (intercept model)	-19375.10	38774.94	38765.41	
2	Squared growth on fixed component and linear growth on random component	-18619.15	37312.56	37283.96	11.76, 88.24
2	Linear growth on fixed and mixture components	-18645.49	37356.99	37331.57	11.91, 88.09
2	Squared growth on fixed component	-18660.57	37378.90	37356.65	12.38, 87.62
2	Linear growth on fixed component	-18681.20	37411.91	37392.84	12.25, 87.75
2	Linear growth on fixed and mixture components	-18681.10	37419.94	37397.70	12.41, 87.59
2	No growth (intercept model)	-18748.38	37538.00	37522.12	12.75, 87.25
2	Linear growth on fixed, random and mixture components	-19280.53	38635.30	38606.70	47.36, 52.64
3	**Linear growth on fixed and mixture components**	**-18433.39**	**36949.29**	**36917.51**	**6.01, 77.35**
3	Squared growth on fixed component and linear growth on random component	-18619.15	37329.06	37294.10	0, 87.46
3	Linear growth on fixed and random components	-18645.49	37373.49	37341.71	0, 87.33
3	Squared growth on fixed and mixture components	-18645.46	37389.93	37351.80	0, 88.01
3	Squared growth on fixed component	-18660.57	37395.40	37366.80	0, 86.83
3	Linear growth on fixed component	-18681.20	37428.41	37402.99	0, 87.30
3	No growth (intercept model)	-18748.38	37554.50	37532.26	0, 86.49
4	Linear growth on fixed and mixture components	-18355.78	36818.80	36777.49	4.34, 73.90
4	Linear growth on fixed and random components	-18404.14	36907.28	36869.15	0, 77.46
4	Linear growth on fixed, random and mixture components	-18645.46	37414.68	37367.01	0, 86.29

4	Linear growth on fixed component	-18681.20	37444.91	37413.13	0, 85.06
4	No growth (intercept model)	-18748.38	37571.00	37542.41	0, 85.55
5	Squared growth on fixed component and linear growth on random component	-18372.06	36867.86	36820.20	0, 76.54
5	Linear growth on fixed and random components	-18404.14	36923.78	36879.29	0, 75.31
5	Squared growth on fixed component	-18417.12	36941.50	36900.19	0, 75.29
5	No growth (intercept model)	-18505.33	37101.41	37066.45	0, 76.28
5	Linear growth on fixed, random and mixture components	-18645.46	37439.43	37382.23	0, 85.08
5	Linear growth on fixed component	-18681.20	37461.41	37423.28	0, 84.64

Women

Number of trajectory classes	model specifications*	Loglik	BIC	SABIC	% participants in classes
1	Linear growth on fixed and random components	-26003.90	52058.27	52039.20	
1	Squared growth on fixed component and linear growth on random component	-26003.06	52064.98	52042.74	
1	Linear growth on fixed component	-26011.52	52056.68	52043.97	
1	Squared growth on fixed component	-26010.79	52063.63	52047.74	
1	No growth (intercept model)	-26078.12	52181.47	52171.93	
2	Linear growth on fixed, random and mixture components	-25518.43	51112.55	51083.95	16.75, 83.25
2	Linear growth on fixed and random components	-25526.02	51119.32	51093.90	17.20, 82.80
2	Linear growth on fixed component	-25547.41	51145.28	51126.22	17.80, 82.20
2	Linear growth on fixed and mixture components	-25545.05	51148.97	51126.73	17.53, 82.47
2	No growth (intercept model)	-26078.12	52198.29	52182.40	42.26, 57.74
3	**Linear growth on fixed and mixture components**	**-25400.65**	**50885.40**	**50853.62**	**10.54, 68.21**
3	Linear growth on fixed, random and mixture components	-25518.43	51137.77	51099.64	0, 81.69
3	Linear growth on fixed and random components	-25526.02	51136.14	51104.36	0, 81.06
3	Linear growth on fixed component	-25547.41	51162.10	51136.68	0, 80.26

3	Squared growth on fixed component	-25546.33	51168.35	51139.75	0, 80.22
3	No growth (intercept model)	-25613.53	51285.93	51263.68	0, 78.77
4	Squared growth on fixed component and linear growth on random component	-25391.46	50892.24	50850.93	0, 68.32
4	Linear growth on fixed component	-25410.23	50904.54	50872.77	0, 67.08
4	No growth (intercept model)	-25467.23	51010.14	50981.55	0, 66.07
4	Linear growth on fixed and random components	-25526.02	51152.96	51114.82	0, 80.33
4	Linear growth on fixed, random and mixture components	-25518.43	51163.00	51115.34	0, 81.13
5	Linear growth on fixed and random components	-25393.92	50905.57	50861.08	0, 63.71
5	Linear growth on fixed component	-25410.23	50921.36	50883.23	0, 61.10
5	Squared growth on fixed component	-25409.01	50927.34	50886.03	0, 60.84
5	No growth (intercept model)	-25467.23	51026.96	50992.01	0, 66.07

Note. The LCMM solution in bold face showed the better fit to data.

Loglik = Loglikelihood value of model convergence; BIC = Bayesian information criterion; SABIC = Sample-adjusted BIC.

* Model specifications were set in base of Carriere et al. (2016) but just considering unstructured, class-specific effects on covariance matrixes. As a result, a total of 160 models (80 models for men sample and 80 models for women) for each sample were estimated. We displayed here models which reached convergence. Fixed component refers to mean trajectory of the population. Random component refers to subject-specific trajectory. Mixture component refers to class-specific trajectory of the population.

Table S3. LCMM factor loadings by trajectory class.

	Men			Women		
	Class 1 (normative)	Class 2 (subclinical)	Class 3 (clinical)	Class 1 (normative)	Class 2 (subclinical)	Class 3 (clinical)
n (%)	2961 (77.35)	637 (16.64)	230 (6.01)	3062 (68.21)	954 (21.25)	473 (10.54)
Mean probability of class membership	.96	.83	.90	.91	.78	.86
Class-specific coefficients						
Intercept (*se*)	-4.83 (0.69)***	-4.20 (0.69)***	-1.07 (0.10)***	-4.06 (0.45)***	-3.66 (0.47)***	-0.80 (0.08)***
Time effect (*se*)	0.02 (0.00)***	0.04 (0.00)***	0.01 (0.01)	0.02 (0.00)***	0.03 (0.00)***	0.01 (0.01)

Note. *se* = Standard error of coefficient. Intercept and slope loadings were tested using *Z* Wald tests.

*** $p < .001$.

Table S4. Comparison summary based on ΔCFI to select the measurement invariance models by sex.

	Weak MI	Strong MI			Strict MI			Fit indexes of selected model
		Level	Slope	Full	Level	Slope	Full	
Self-reported health								
Men		-0.193	-0.001	-0.780	0.026	**-0.001**	0.364	χ^2 (13) = 16.36, RMSEA = .026, CFI = .99, TLI = 1.00
Women		-0.370	-0.002	-0.005	0.070	**0.002**	0.467	χ^2 (13) = 8.99, RMSEA = .000, CFI = 1.00, TLI = 1.00
Multimorbidity								
Men		0.000	0.000	-0.026	0.000	**0.000**	-0.033	χ^2 (27) = 52.66**, RMSEA = .049, CFI = .98, TLI = .99
Women		-0.004	0.000	-0.060	0.001	**0.000**	-0.020	χ^2 (27) = 68.22**, RMSEA = .053, CFI = .98, TLI = .98
Loneliness								
Men	**0.000**		-0.083			-0.089		χ^2 (2) = 0.26, RMSEA = .000, CFI = 1.00, TLI = 1.00
Women	-0.113		-0.161			-0.122		χ^2 (2) = 0.01, RMSEA = .000, CFI = 1.00, TLI = 1.00
Visual function								
Men		0.001	0.016	-0.143	-0.003	**0.000**	0.056	χ^2 (27) = 26.18, RMSEA = .000, CFI = 1.00, TLI = 1.00
Women		-0.074	**0.000**	-0.380	-0.014	-0.014	0.105	χ^2 (17) = 20.24, RMSEA = .019, CFI = 1.00, TLI = 1.00
Hearing function								
Men		-0.016	**0.000**	-0.034	-0.004	-0.006	0.010	χ^2 (17) = 29.59*, RMSEA = .043, CFI = .99, TLI = .99
Women		-0.019	**0.001**	-0.077	-0.002	-0.003	0.029	χ^2 (17) = 24.83, RMSEA = .029, CFI = 1.00, TLI = 1.00

Note. ΔCFI values between each solution and the less constrained one (weak MI models vs. unconstrained; strong MI vs. weak MI or unconstrained; strict MI models vs. strong MI ones) are displayed in rows. The selected models were in bold face. Decision on selection was taken by means of the comparison index (ΔCFI) and absolute fit indexes of each model. Fit indexes of the selected model are displayed. The unconstrained model fitted better in the case of loneliness models for women.

Weak MI = Weak measurement invariance (only for loneliness models), with loadings constrained. Strong MI = Strong measurement invariance, with intercepts (and loadings for loneliness models) constrained. Strict MI = Strict measurement invariance, with intercepts and variances constrained (and loadings for loneliness models).

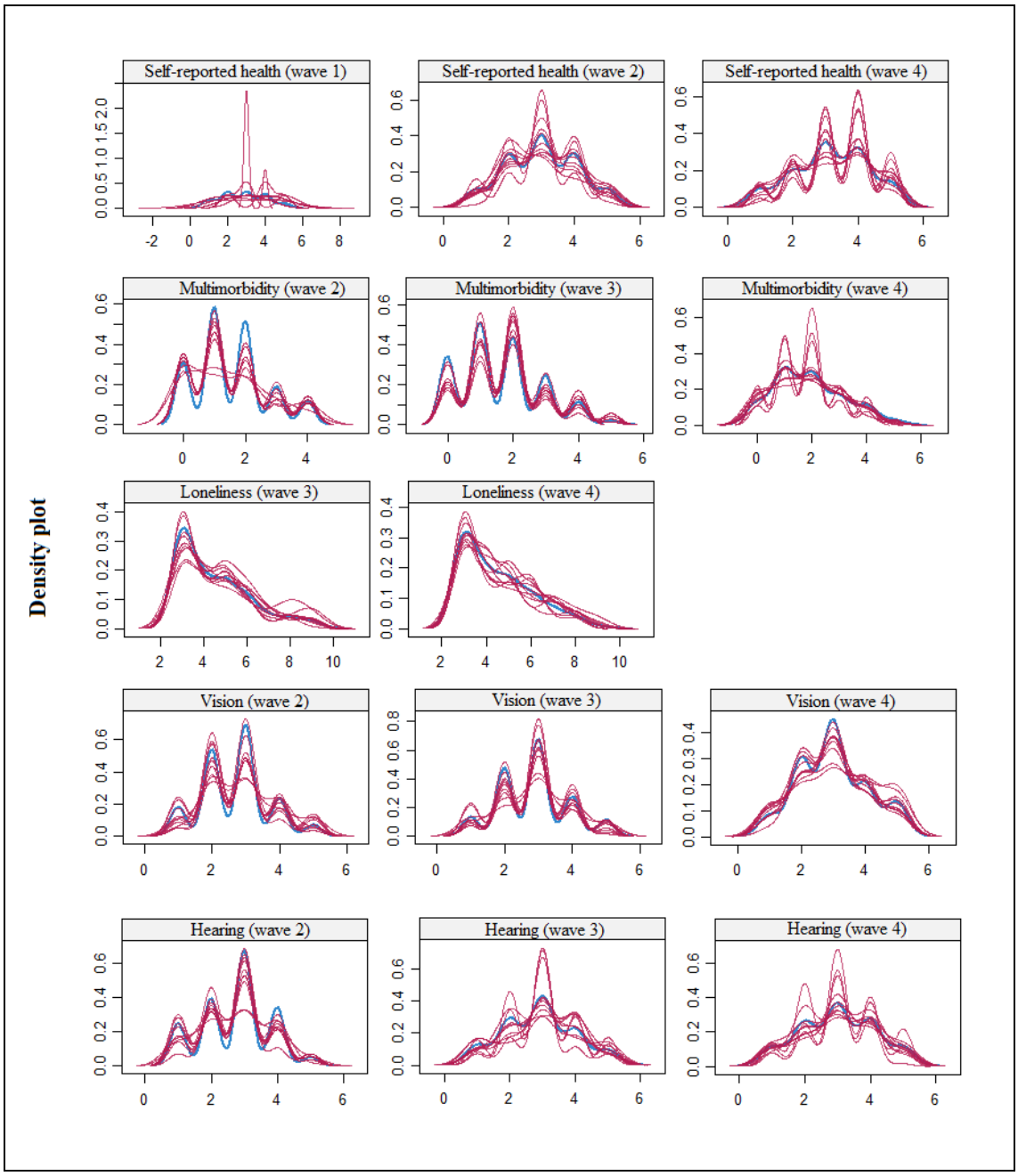
Strong and strict models relied on partial measurement invariance (except in the case of loneliness), constraining parameters other on the latent variable 'level', or on the latent variable 'slope', or in both variables ('full').

All the absolute fit indexes were scaled. RMSEA = root mean square error of approximation. CFI = Comparative fit index. TLI = Tucker-Lewis index.

* $p < .05$; ** $p < .01$.

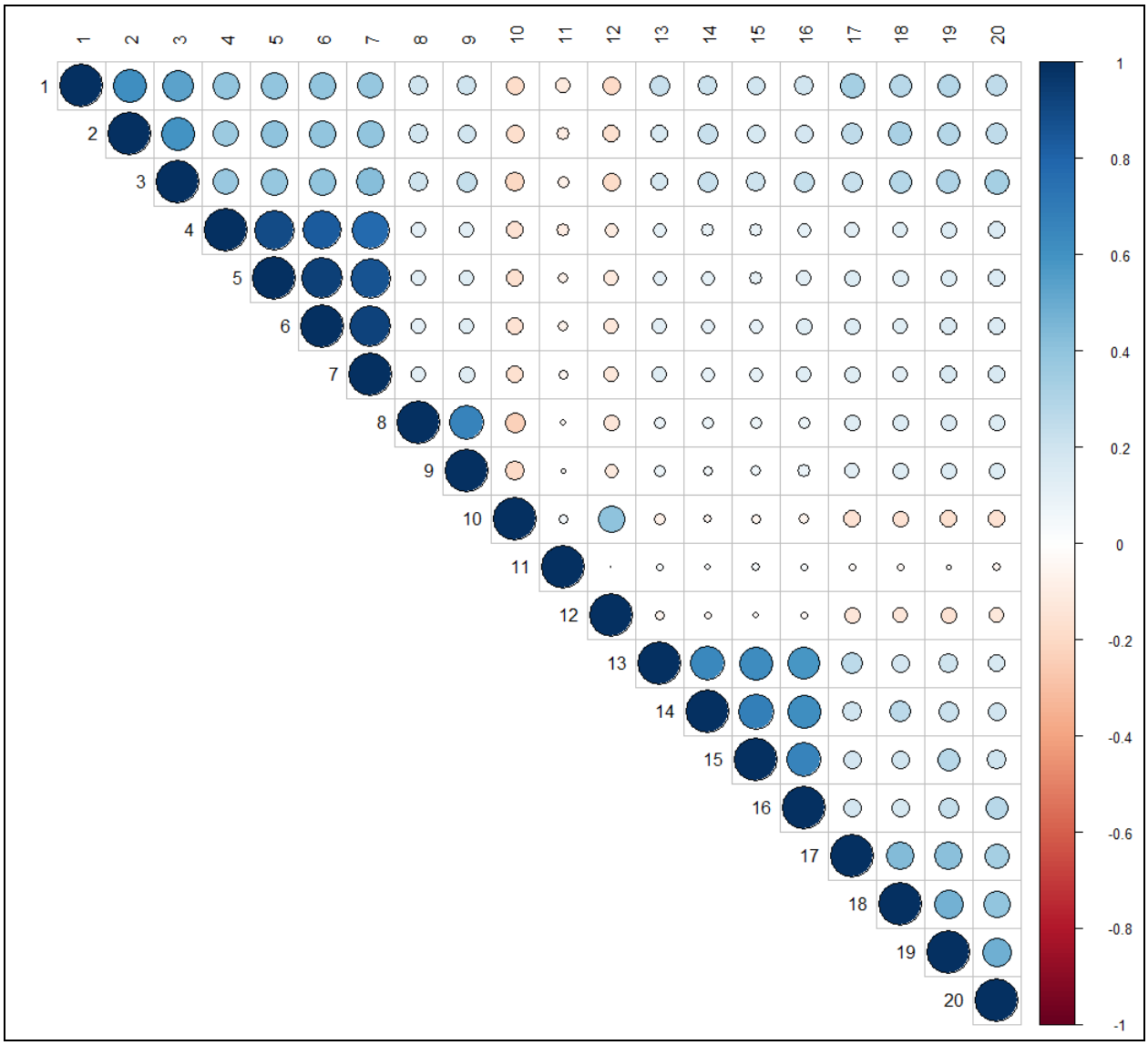
Coefficients for the MI models are available upon corresponding author request.

Figure SF1. Density plot of observed and imputed data.



Note. This figure displays the cumulative density distribution of observed data, in blue ink; and those from imputed data (all iterations), in red ink. Data were imputed from the 14 variables.

Figure SF2. Correlations between factor profile predictors.



Note. Spearman coefficients were used due to the presence of non-continuous factors (or with non-normal distribution).

1 = Self-reported health (wave 1); 2 = Self-reported health (wave 2); 3 = Self-reported health (wave 4); 4 = Multimorbidity (wave 1); 5 = Multimorbidity (wave 2); 6 = Multimorbidity (wave 3); 7 = Multimorbidity (wave 4); 8 = Loneliness (wave 3); 9 = Loneliness (wave 4); 10 = Household income; 11 = Retirement age; 12 = Educational level; 13 = Hearing functioning (wave 1); 14 = Hearing functioning (wave 2); 15 = Hearing functioning (wave 3); 16 = Hearing functioning (wave 4); 17 = Visual functioning (wave 1); 18 = Visual functioning (wave 2); 19 = Visual functioning (wave 3); 20 = Visual functioning (wave 4).